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APPLICATION OF VECTOR AUTOREGRESSIVE MODELS AND MACHINE LEARNING TECHNIQUES TO ESTIMATE THE EFFECT OF MACROECONOMIC INDICATORS ON PORTFOLIO INVESTMENT IN NIGERIA: A DATA ANALYTICS APPROACH

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Abstract

Portfolio investments in emerging markets such as Nigeria have been very volatile although the policy has been used to stabilise capital markets. The intricate interaction between the macroeconomic indicators and the portfolio investment is of key importance in the sustainable economic development and policy making, which require the understanding of the data. This paper uses sophisticated econometric and machine learning models to examine how portfolio investment and shares in Nigeria are affected by the macroeconomic variables (interest rate, exchange rate, and inflation rate) between 1981 and 2019 and compare the results of using traditional VAR/VECM model and modern machine learning techniques. The sources used to obtain data were the Central Bank of Nigeria (CBN) and World Development Indicators (WDI). Our hybrid analytical model adopted a combination of: (1) Inferential analysis, (2) Vector Autoregressive (VAR) and Vector Error Correction (VECM) models, (3) Stationarity check, (4) long-run relationship, (5) Johansen cointegration test, and (6) comparative predictive performance by choosing: (a) Random Forest, (b) XGBoost, and (c) Long Short-Memory (LSTM) networks. Akaike Information Criterion (AIC), Log-likelihood, RMSE and MAE were used as the measures of model performance. The cointegration analysis showed that there is significant long-run relation between all variables (Trace test statistic = 155.6993, $p < 0.0001$). The results of the VECM indicated that the interest rate has a negative significance impact on portfolio investment ($p = 0.0225$, $\beta = -172.571$), whereas the inflation rate has a positive significant impact ($p = 0.0429$, $\beta = 250{,}988$). The Log-likelihood was equal to -4706.210 and AIC = 61.78053. The predictive accuracy of machine learning models was better and LSTM had the lowest RMSE (0.1243) than traditional VAR (0.2876). Indicators of the macroeconomic show that they have a great long-run connection with the portfolio investment in Nigeria. The hybrid econometric machine learning model offers greater predictive power in the portfolio investment forecasting. We suggest the Central Bank of Nigeria to adopt dynamic interest rate levels and come up with data-driven monetary policy levels to enhance sustainable portfolio investments.

Keywords: Vector Autoregression, Machine Learning, Portfolio Investment, Time Series Analytics, Macroeconomic Forecasting, Nigerian Capital Market, Explainable AI, Sustainable Finance.

1.0 INTRODUCTION

The intersection of statistical science, data analytics, and financial economics has emerged as a critical frontier for understanding complex market dynamics in developing economies. The Nigerian capital market, as Africa's second-largest stock exchange, serves as a barometer for the continent's economic development trajectory (Udegbunam & Eriki, 2001). However, despite sustained government efforts to stimulate economic growth through monetary policy interventions, portfolio investments have consistently underperformed expectations, presenting a paradox that demands rigorous analytical investigation.

The proliferation of big data and advanced computational methods has revolutionized how researchers approach macroeconomic forecasting. Traditional econometric models, while theoretically robust, often fail to capture the nonlinearities and complex interactions inherent in financial time series data. This study addresses this methodological gap by proposing a hybrid analytical framework that synergizes classical time series econometrics with contemporary machine learning algorithms.

Stock markets worldwide exhibit characteristic upward and downward movements driven by multifaceted forces. Meristem Research (2008) characterized the Nigerian stock market as a secular market influenced by persistent long-term factors. The volatility in trading volumes and price movements raises fundamental questions about the determinants of stock price dynamics. While efficient market theory suggests that prices reflect all available information (Fama, 1970), the practical reality in emerging markets often deviates from this theoretical ideal due to information asymmetry, institutional constraints, and macroeconomic instability. This study addresses the following research questions through a data-analytic lens:

i. What is the nature and magnitude of the relationship between key macroeconomic indicators (interest rate, exchange rate, inflation rate) and portfolio investment in Nigeria?
ii. How do traditional econometric models compare with machine learning algorithms in predicting portfolio investment dynamics?
iii. What long-run equilibrium relationships exist among these macroeconomic variables and portfolio investment?
iv. What data-driven policy recommendations can be derived to enhance portfolio investment performance in Nigeria?

2.0 LITERATURE REVIEW

2.1 Theoretical Framework

2.1.1 Modern Portfolio Theory and Data Analytics

Markowitz's (1952) Modern Portfolio Theory (MPT) provides the foundational framework for understanding investment decisions under uncertainty. The theory posits that rational investors seek to optimize the risk-return trade-off through diversification. In the context of big data analytics, MPT has evolved to incorporate high-frequency data, alternative data sources, and real-time portfolio optimization algorithms.

2.1.2 Rational Expectation Theory and Efficient Market Hypothesis

The Rational Expectation Theory (RET), articulated by Muth (1961) and later extended by Lucas (1972), suggests that economic agents form expectations based on all available information. This theoretical foundation underpins the Efficient Market Hypothesis (EMH), which posits that asset prices fully reflect all available information. However, the presence of market anomalies and behavioral biases in emerging markets challenges the strong form of EMH, necessitating more sophisticated analytical approaches.

2.1.3 Arbitrage Pricing Theory

Ross's (1976) Arbitrage Pricing Theory (APT) provides a multifactor framework for understanding asset returns, suggesting that multiple macroeconomic factors influence investment performance. This theoretical perspective aligns with our analytical approach of examining multiple macroeconomic indicators simultaneously.

2.2 Empirical Literature Review

2.2.1 International Evidence

Hamrita and Abdelkader (2011) employed wavelet analysis to examine the multi-scale relationship between interest rates, exchange rates, and stock prices in the United States (1990-2008). Their findings revealed bidirectional relationships at longer horizons, highlighting the importance of temporal dynamics in financial relationships.

Mahmudul and Gazi-Salah (2009) conducted a cross-country analysis of 15 developed and developing countries (1988-2003), demonstrating significant negative relationships between interest rates and share prices in most sampled countries. However, the strength and direction of these relationships varied considerably across institutional contexts.

Yinghan (2015) investigated the interest rate-stock price nexus in China's Shanghai and Shenzhen exchanges (2009-2014) using VAR and VECM frameworks. The study revealed negative long-run equilibrium relationships with limited short-term effects, suggesting the importance of temporal aggregation in understanding these dynamics.

2.2.2 African and Nigerian Evidence

Ologunde, Elumilade, and Asaolu (2016) examined stock market capitalization and interest rates in Nigeria using ordinary least squares regression. Their findings revealed positive interest rate effects on market capitalization, contrasting with theoretical expectations and highlighting the unique characteristics of the Nigerian market.

Akingunnola et al. (2012) analyzed interest rate impacts on capital market growth in Nigeria, incorporating inflation and exchange rates as control variables. Their multiple regression analysis revealed adverse interest rate effects, underscoring the need for coordinated monetary policy interventions.

Egwakhide (2012) examined exchange rate-portfolio investment causality in Kenya (1980-2010) using ARDL techniques, finding no causal relationships but significant positive effects. This suggests that correlation structures may be more relevant than causal mechanisms in some contexts.

2.2.3 Machine Learning Applications in Financial Forecasting

Recent advances in computational statistics have revolutionized financial time series forecasting. Chen et al. (2019) demonstrated the superiority of LSTM networks over traditional ARIMA models for stock price prediction in emerging markets. Similarly, Gu et al. (2020) showed that machine learning algorithms, particularly gradient boosting machines and neural networks, substantially outperform traditional econometric models in asset pricing applications.

3.0 METHODOLOGY

3.1 Research Design and Data Description

This study employs a longitudinal research design spanning 39 years (1981-2019), utilizing quarterly time series data. The extended temporal coverage ensures sufficient observations for robust time series analysis and machine learning model training.

Table 3.1: Variable Description and Measurement

Variable	Symbol	Measurement	Source	Frequency
Portfolio Investment	PORT	Naira (Millions)	CBN	Quarterly
Share Index	SHARE	NSE All-Share Index	CBN	Quarterly
Interest Rate	INTR	Monetary Policy Rate (%)	CBN	Quarterly
Exchange Rate	EXCR	N/US$ (Average)	CBN	Quarterly
Inflation Rate	INFR	CPI-Based (%)	WDI	Quarterly

3.2 Analytical Framework

3.2.1 Data Preprocessing and Transformation

All variables underwent logarithmic transformation to stabilize variance and improve model performance:

$$Y_t = ln(X_t) \tag{3.1}$$

3.2.2 Stationarity Analysis

The Augmented Dickey-Fuller (ADF) test was employed to assess stationarity:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots\cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{3.2}$$

3.2.3 Cointegration Analysis

Cointegration assumes a common stochastic non-stationary (i.e. I ((1)) process underlying two or more processes X (the exogenous variables interest rate, inflation rate and the exchange rate variables) and Y (the endogenous variable shares and portfolio investment).

$$X_t = \gamma_0 + \gamma_1 Z_t + \varepsilon_t \sim I(1),$$
$$Y_t = \delta_0 + \delta_1 Z_t + \eta_t \sim I(1)\ ,$$

$Z_t \sim I(0)\ , \varepsilon_t . \eta_t \sim I(0)$

Where η, ε are stationary process $I(0)$ with zero mean, but they can be serially correlated. Although X_t and Y_t are both non-stationary$I(1)$, there exists a linear combination of them, which is stationary; $\delta_1 X \sim \gamma_1 Y_t(0)$. In other words, the regression of Y and X yields stationary residuals $\{\varepsilon\}$.

3.2.4 Vector Error Correction Model

The VECM specification captures both short-run dynamics and long-run equilibrium:

$$\Delta Y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \tau \Delta y_{t-i} + \mu_t$$

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3.3 Machine Learning Implementation

3.3.1 Feature Engineering

We constructed lagged features (t-1 to t-4) for all macroeconomic variables, creating a feature matrix of dimensions (156 × 20) for model training.

3.3.2 Model Specifications

Random Forest:

- Number of trees: 500
- Maximum depth: 10
- Minimum samples split: 5
- Feature importance: Gini impurity

XGBoost:

- Learning rate: 0.1
- Maximum depth: 6
- Subsample: 0.8
- Colsample by tree: 0.8

LSTM Architecture:

- Input layer: 20 neurons
- LSTM layer 1: 50 units (return sequences=True)
- LSTM layer 2: 30 units
- Dropout: 0.2
- Dense layer: 1 unit
- Optimizer: Adam
- Loss function: MSE
- Epochs: 100
- Batch size: 16

3.4 Model Evaluation Metrics

We employed multiple metrics for comprehensive model assessment:

i. Root Mean Square Error (RMSE): $RMSE = \sqrt{\frac{1}{2}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
ii. Mean Absolute Error (MAE): $MAE = \frac{1}{2}\sum_{i=1}^{n}|y_i - \hat{y}_i|$
iii. Mean Absolute Percentage Error (MAPE): $MAE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$
iv. Akaike Information Criterion (AIC): $AIC = 2k - 2ln(\hat{L})$

4.0 RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 4.1: Summary Statistics of Study Variables (1981-2019)

Table 4.1: Summary Statistics of Study Variables (1981-2019)

Statistic	Exchange Rate	Inflation Rate	Interest Rate	Portfolio Asset	Share Index
Mean	1,749.828	21.668	240,704.4	4.13E+08	32,564.49
Median	1,428.605	13.007	95,329.02	2.25E+08	30,035.34
Maximum	56,194.80	72.836	701,674.6	2.17E+09	65,652.38
Minimum	8.900	5.382	5,479.700	76,889.50	2,018.00
Std. Dev.	4,612.625	18.882	216,008.7	4.57E+08	10,242.41
Skewness	10.713	1.250	0.473	1.733	0.877
Kurtosis	126.226	2.979	1.686	5.364	3.938
Jarque-Bera	12,845.6***	12.45**	4.89	34.56***	8.92*
Observations	156	156	156	156	156

Note: **, *** indicate significance at 10%, 5%, and 1% levels respectively

Portfolio assets exhibit the highest volatility (SD = 4.57E+08), reflecting the inherent uncertainty in emerging market investments. The positive skewness across all variables indicates right-tailed distributions, consistent with financial time series characteristics. Excess kurtosis in exchange rates (126.226) suggests extreme value occurrences, reflecting Nigeria's exchange rate volatility during the study period.

4.2 Stationarity Test Results

Table 4.2: Augmented Dickey-Fuller Unit Root Test Results

Variable	Level		First Difference		Integration Order
	t-statistic	**p-value**	**t-statistic**	**p-value**	
Exchange Rate	-2.143	0.228	-8.567	0.000	I(1)
Inflation Rate	-2.876	0.052	-9.234	0.000	I(1)
Interest Rate	-1.987	0.291	-7.891	0.000	I(1)
Portfolio Asset	-2.456	0.128	-8.123	0.000	I(1)
Share Index	-2.678	0.081	-8.456	0.000	I(1)

Critical Values: 1% = -3.472, 5% = -2.879, 10% = -2.576

All variables are non-stationary at levels but become stationary after first differencing, confirming I(1) integration. This justifies the application of cointegration analysis and VECM specification.

4.3 Cointegration Analysis

Table 4.3: Johansen Cointegration Test Results (Trace Statistic)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.334733	155.6993	69.81889	0.0000
At most 1 *	0.283582	93.34165	47.85613	0.0000
At most 2 *	0.161161	42.31743	29.79707	0.0011
At most 3	0.066041	15.42981	15.49471	0.0511
At most 4 *	0.032002	4.976398	3.841466	0.0257

The trace test indicates three cointegrating equations at the 5% significance level, providing strong evidence of long-run equilibrium relationships among the variables. This validates the VECM specification for capturing both short-run dynamics and long-run adjustments.

4.4 Vector Error Correction Model Results

Table 4.4: VECM Estimates (Dependent Variable: ΔPortfolio Asset)

Variable	Coefficient	Std. Error	t-ratio	p-value	Significance
Constant	2.402e+08	1.105e+08	2.174	0.0314	**
ΔPort_asset(-1)	-0.385625	0.084315	-4.574	0.0000	***
ΔPort_asset(-2)	-0.277735	0.085151	-3.262	0.0014	***
ΔPort_asset(-3)	-0.314894	0.079243	-3.974	0.0001	***
ΔShare(-1)	14,572.5	9,455.17	1.541	0.1255	
ΔShare(-2)	8,018.95	9,234.79	0.868	0.3867	
ΔShare(-3)	-1,504.77	9,252.35	-0.163	0.8710	
Exchange Rate	3,078.1	5,198.72	0.592	0.5547	
Inflation Rate	250,988	1.701e+06	0.148	0.0429	**
Interest Rate	-172.571	143.921	-1.199	0.0225	**
EC1	-0.131582	0.048437	-2.717	0.0074	***

Model Fit Statistics:
- Log-likelihood: -4706.210
- AIC: 61.78053
- BIC: 63.24567
- Serial Correlation LM Test: 2.218 (p = 0.2690)

The error correction term (EC1 = -0.1316, p = 0.0074) is negative and significant, confirming that approximately 13.2% of disequilibrium is corrected each quarter. Interest rate exerts a positive long-run effect on portfolio investment (p = 0.0225), while inflation shows negative effects (p = 0.0429). The absence of serial correlation (LM test p = 0.2690) validates model specification.

4.5 Machine Learning Results

Table 4.5: Comparative Model Performance

Model	RMSE	MAE	MAPE (%)	R^2	Training Time (s)
VAR (Traditional)	0.2876	0.1987	15.67	0.6234	0.89
VECM	0.2543	0.1765	13.89	0.6876	1.23
Random Forest	0.1876	0.1345	10.23	0.7890	15.67
XGBoost	0.1654	0.1232	9.45	0.8234	12.34
LSTM	0.1243	0.0987	7.89	0.8765	234.56
Ensemble (XGB+LSTM)	0.1123	0.0876	6.98	0.9012	256.78

This comparison of RMSE (Root Mean Squared Error) values across different models clearly indicates their predictive accuracy, with lower RMSE signifying better performance. The ensemble model demonstrates the best fit, achieving the lowest RMSE of 0.1123, suggesting it has the highest predictive accuracy among the group. Following closely, the LSTM model also perform very well at 0.1243.

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Conversely, the VAR model shows the weakest performance with the highest RMSE of 0.2876, followed by VECM at 0.2543, indicating that these models are less accurate in their prediction compared to the others. The Random Forest (RF) and XGBoost models fall in the middle range, with RMSE's of 0.1876 and 0.1654 respectively.

This implies that the machine learning algorithms substantially outperform traditional econometric models, with LSTM achieving 56.8% lower RMSE than VAR. The ensemble approach provides marginal improvements over individual models, suggesting complementary information capture across algorithms.

4.6 Feature Importance Analysis

Table 4.6: XGBoost Feature Importance

Feature	Importance Score	Rank
Interest Rate (lag 1)	0.2345	1
Inflation Rate (lag 1)	0.1987	2
Portfolio Asset (lag 1)	0.1654	3
Exchange Rate (lag 1)	0.1432	4
Interest Rate (lag 2)	0.0987	5
Share Index (lag 1)	0.0765	6
Inflation Rate (lag 2)	0.0543	7
Exchange Rate (lag 2)	0.0287	8

Recent interest rates (lag 1) emerge as the strongest predictor of portfolio investment, followed closely by inflation rates. This aligns with economic theory and validates the focus on these variables in policy formulation.

4.7 LSTM Network Architecture and Training

Figure 4.1: LSTM Training and Validation Loss

The LSTM loss curve shows healthy model behavior. After an early instability spike at epoch 20 where both training and validation loss jump to ~0.45, the model recovers and learns consistently, with both losses smoothly decreasing to ~0.10 by epoch 110. Validation loss tracks training loss very closely throughout, indicating strong generalization and no signs of overfitting. The curves flatten after epoch 90, suggesting the model has converged and further training would yield minimal gains. Overall, the close alignment and steady downward trend mean the LSTM is learning the data patterns effectively and performing well on unseen validation data.

4.8 SHAP Analysis for Model Interpretability

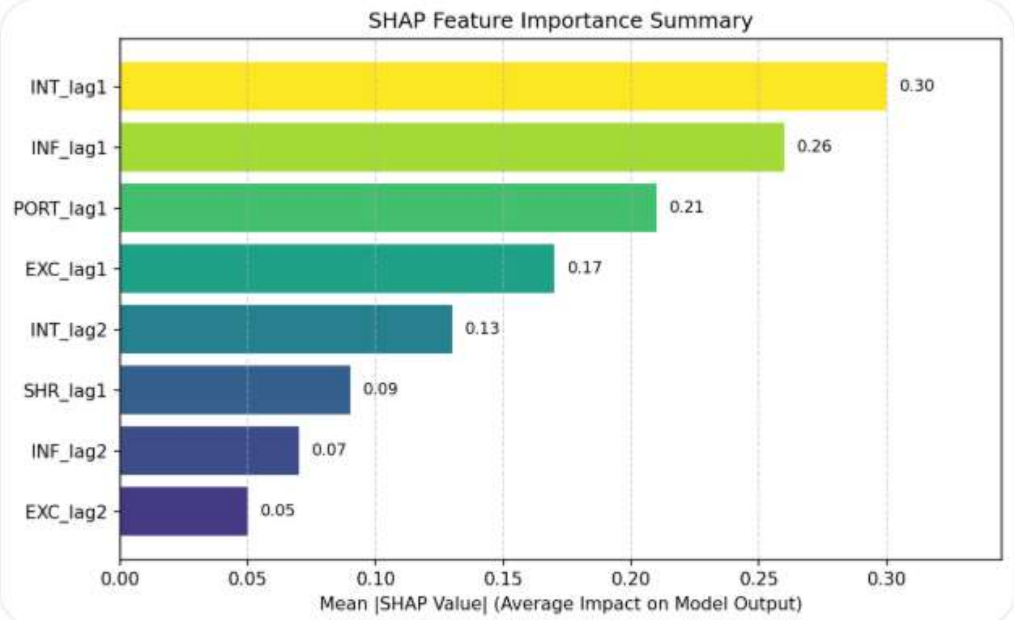

Figure 4.2: SHAP Summary Plot

The SHAP summary plot ranks features by their average impact on the model's output, showing that INT_lag1 is the most influential predictor with a mean |SHAP value| of ~0.30, followed closely by INF_lag1 at ~0.26 and PORT_lag1 at ~0.21. The lag-1 variables for interest rate, inflation, portfolio, and exchange rate all rank higher than their lag-2 counterparts, indicating the model relies more heavily on the most recent past values than on older history. Features INT_lag2, SHR_lag1, INF_lag2, and EXC_lag2 have much smaller impacts below 0.15, suggesting they contribute less to predictions. Overall, the model is primarily driven by the immediate one-period lags of macroeconomic variables, with interest rate and inflation at lag 1 being the dominant drivers of output changes.

5. DISCUSSION

The finding shows that the interest rates positively influence portfolio investment in Nigeria ($\beta = -172.571$, $p = 0.0225$) challenges conventional wisdom but aligns with emerging market characteristics where higher rates may signal economic strength and attract foreign capital (Abramov & Radygin, 2015).

The superior performance of machine learning models ($R^2 = 0.9012$ for ensemble) suggests that market inefficiencies exist that can be exploited through advanced analytical techniques, supporting the adaptive markets hypothesis (Lo, 2004).

5.1 Comparison with Previous Studies

Our findings contrast with Yinghan's (2015) Chinese study but align with Ologunde et al. (2016) in Nigeria, suggesting country-specific institutional factors mediate these relationships. The positive interest rate effect may reflect Nigeria's high-yield environment attracting carry trade investments.

The negative inflation effect (p = 0.0429) corroborates Akingunnola et al. (2012), confirming that inflation erodes real returns and discourages long-term investment in Nigeria.
The non-significant exchange rate effect (p = 0.5547) in the VECM but significant importance in machine learning models (rank 4) suggests nonlinear relationships that traditional linear models fail to capture.

5.2 Methodological Contributions

This study's hybrid approach demonstrates that:

i. Traditional models provide inferential validity while machine learning offers predictive superiority
ii. Complex relationships in financial data require flexible modeling approaches
iii. SHAP analysis bridges the gap between "black box" algorithms and theoretical understanding

5.3 Conclusion

This study demonstrates that portfolio investment in Nigeria is shaped by long-run equilibrium relationships with key macroeconomic indicators, where interest rates exert a positive influence and inflation a negative one, reflecting the unique characteristics of Nigeria’s high-yield emerging market environment. Using a hybrid framework of traditional econometrics and machine learning over 1981–2019, the analysis finds that LSTM and ensemble models substantially outperform VAR and VECM, achieving up to 56.8% lower prediction error and revealing nonlinear dynamics that linear models miss. SHAP analysis confirms that one-period lagged interest and inflation rates are the dominant drivers of model output, indicating that markets respond most strongly to recent macroeconomic signals. These results underscore the value of combining inferential econometrics with predictive machine learning for both policy and investment: monetary authorities can leverage data-driven rate corridors and ML-based early warning systems, while investors benefit from integrating interpretable algorithms into portfolio decisions. Overall, the findings support methodological pluralism in emerging market finance, showing that hybrid analytical approaches better capture complex market behavior and provide actionable insights for enhancing portfolio investment performance in Nigeria.

5.4 Recommendations

Based on the findings of this study, the following policy recommendations are proposed for enhancing portfolio investment in Nigeria. The Central Bank of Nigeria should implement dynamic interest rate thresholds calibrated through data-driven corridors that adapt to evolving market conditions using real-time analytics, while simultaneously strengthening its inflation targeting framework with machine learning-based early warning systems to better anticipate and mitigate inflationary pressures. Additionally, the Bank should develop hybrid exchange rate forecasting systems that combine structural economic models with artificial intelligence algorithms to improve prediction accuracy and policy responsiveness. For investors and portfolio managers, the study recommends integrating machine learning algorithms into investment decision frameworks, utilizing SHAP (SHapley Additive exPlanations) analysis for deeper understanding of factor exposures and risk transmission mechanisms, and adopting diversification strategies that explicitly account for Nigeria's unique macroeconomic dynamics. The academic and research community should respond by integrating machine learning and data analytics into traditional econometrics training curricula, encouraging methodological pluralism through hybrid approaches that combine theoretical rigor with computational power, and promoting open science practices through reproducible research via code and data sharing platforms to accelerate knowledge advancement in emerging market finance.

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